Uncertainties in LCA (Subject Editor: Andreas Ciroth)

Fuzzy-Sets Approach to Noise Impact Assessment

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Abstract

Background, Aims and Scope. Noise impacts are rarely assessed in Life Cycle Assessment (LCA), probably due to lack of data, to the difficulty of setting up an appropriate assessment method including relevant uncertainties and vagueness and to their site-dependent nature. The evaluation, as well as for odour, cultural and aesthetic impacts, seems to be closely related to human judgements and perception based. Although fuzzy-sets have been developed for this purpose since the late '60s and their usefulness has been proven by successful applications, noise impact assessment approaches have been essentially crisp so far. The aim of this paper is to present a method for noise impact assessment based on fuzzy sets with an application to a simple example.

Methods. The fuzzy noise impact assessment involves: 1) the quality assessment of the site concerned by the noise impact before the occurrence of noise emissions; quality is expressed by a crisp (i.e. non-fuzzy) function depending on variables (the so-called 'primitives'), which are relevant for the evaluation (e.g. the population density, the type of land use, ...); 2) the fuzzy representation of the primitives, e.g. their evaluation by means of linguistic variables (such as 'the population density is high') and by fuzzy numbers; 3) the fuzzy representation of the quality, by fuzzifying the crisp function defined in 1) and 4) the fuzzy representation of the noise impact. In the example, the noise impacts of three processes of coal mining and combustion are assessed.

Results and Discussion. The application example proved the operationability of the method. Primitives and noise impact assessment results are represented by fuzzy numbers and intervals that are more informative than crisp numbers for the interpretation of results The quality and impact assessment results obtained seem to be coherent with the nature of the processes involved and of the variables characterizing them.

Conclusion and Outlook. Fuzzy intervals and numbers could be more informative and closer to human judgements and perceptions than crisp numbers are, thus improving the pertinence and the interpretation of the results. Despite the increase in sophistication and the fact that the representation of the variables involved in calculations should be developed further (e.g. on the basis of consensus gained in an expert panel), the fuzzy approach seems to be promising for the assessment of noise impacts in LCA.

Keywords: Fuzzy sets; noise effects; noise impacts; uncertainty analysis

Introduction

Although two significant attempts were made to assess noise effects of road traffic (Lafleche et al. 1997, Müller-Wenk 2004), noise impacts are rarely considered in LCA. As pointed out by Müller-Wenk, the reasons for this neglect could be mainly the unavailability of appropriate noise assessment methods, as well as the opinion that noise effects are very local and difficult to interpret in relation to other impact categories (Müller-Wenk 2004). Lack of data and uncertainties related to their evaluation could also be considered important reasons.

The evaluation of noise impacts, as well as of odour, cultural and aesthetic ones, seems to be closely related to human judgements and perception based. For example, the nuisance of a noise emission could depend on the type and sensibility of the population exposed. Since the late 60s, fuzzy-sets theory has been developed to represent the vagueness of natural language. The classical set-theory, where it is clearly determined whether an item belongs to the set (e.g. 'one') or not (e.g. 'zero') has been extended, so that in the fuzzy-set theory, membership degrees also exist between zero and one (Zadeh 1965). Numerous studies and successful industrial applications have proven the usefulness of fuzzy-sets in the modelling of human-related and natural systems. During the last years, fuzzy-set approaches have been more and more developed in environmental science, leading to a 'fuzzy boom' in ecological modelling (Silvert 1997, 2000). Fuzzy evaluation of environmental impacts has been investigated, so that approaches (e.g. Borri et al. 1998, De Vita et al. 1995) and methods focusing on specific impact categories or stressors, e.g. pesticides (e.g. van der Werf et al. 1998) were developed. In LCA, fuzzy-sets have already been adopted to better link Life Cycle Inventory (LCI) and Life Cycle Impact Assessment (LCIA) results and to improve LCA calculations by means of fuzzy expert systems (Thiel et al. 1999, Weckenmann et al. 2001).

By considering the results and the perspectives of such approaches, this article presents an original fuzzy-sets approach to noise impact assessment in LCA. First, a general fuzzy impact assessment methodology is briefly introduced. Then, a specific method for noise impact assessment is presented and applied to a simple example.

1 Fuzzy-Sets Approach to Impact Assessment

A general fuzzy-sets approach to environmental impact assessment could include five phases (Enea et al. 2001):

1. the quality assessment of the site studied, prior to the LCI emissions generating the impact, by means of relevant variables, called 'primitives' (for noise impacts: the existing noise, the type of land use, the population density,…). Quality has to be assessed since the magnitude of noise impact, for the same LCI emission, varies according to the initial quality of the site;
2. the fuzzy representation of the primitives, by fuzzy numbers or linguistic variables; for example, the type of land use could be characterized by expressions such as 'almost rural' or 'quiet residential' corresponding to given functions;
3. the fuzzy assessment of the quality, i.e. the aggregation of the fuzzy primitives according to the quality function of step 1, by means of fuzzy aggregation rules;
4. the crisp impact assessment by means of a function depending on the quality of the site, the exposure of the targets and the nuisance of LCI emissions;
5. the fuzzy impact assessment by fuzzifying the crisp function of step 4.

Each step has been widely discussed in literature and will not be considered further in this paper (Canter 1996, Morris et al. 1996, Gupta et al. 1991, Li Xing et al. 1995, Vincent et al. 1997). This general approach is the starting point for the development of a specific method for noise impact assessment in LCA.

2 Fuzzy Noise Impact Assessment in LCA

2.1 Evaluation of the quality of the sound environment

The quality of a site could depend on 1) the existing noise level w expressed as 'weighted decibels with respect to the mean' or 'noise levels' [dBA] (Canter 1996) before the occurrence of the LCI emissions of the unit process related; 2) the type of land use and 3) the population density. The latter two are clearly correlated but, for example, some urban areas could have a significant lower population density than others in a time period, so it seems convenient to consider both. Of course, other primitives could be added in specific situations. In the following, some examples of fuzzy representations of these primitives are presented.

2.1.1 Existing noise level

The range of noise levels of the site concerned by the unit processes studied should be estimated by means of in situ measurements before the occurrence of LCI emissions. Since the measurements are time and resource consuming, the estimations are usually based on literature data. In **Table 1**, for instance, three categories of noise levels with the relative ranges are considered (Canter 1996).

Fuzzy numbers can be defined over these intervals. The membership functions are estimated by the practitioner, considering that the height of a fuzzy number (the highest membership degree) is the most likely value and its shape is usually triangular or trapezoidal. Examples of noise levels are given in Fig. 2c, 3c and 4c.

2.1.2 Type of land use

In order to represent the type of land use, some linguistic variables could be defined, e.g. 'urban', 'residential' and 'rural', whose membership functions, obtained from experts' interviews or knowledge-expert systems on real x-coordinates (e.g. the number of residential houses), could allow an estimation concerning the degree to which the site is 'urban', 'residential' and 'rural'. In this paper, to simplify the calculations, only one linguistic variable 'type of land use' L is considered, defined over the interval [0,2] of abstract x-coordinates l. By definition, when l is close to 0, the type of land use is urban, when l is close to 1, the type of land use is more residential and when l is close to 2, the type of land use is definitively rural. The values assumed by l in the interval correspond to all the nuances between the three. A fuzzy interval associated to the variable 'type of land use' states the membership of the values of l to the set of the variable, i.e. the degree to which the different levels of 'urban', 'residential' and 'rural' belong to the site considered. Examples are given in Fig. 2a, 3a and 4a for the types of land use of Table 3.

2.1.3 Population density

The same type of fuzzy variable used for the evaluation of the type of land use is pertinent for the evaluation of the population density. A variable 'population density' P whose values range in the interval [0,2] of abstract x-coordinates p is considered. By definition, when p is close to 0, the density of population is over 10,000 persons/km^2; when p is close to 1, the density of population is between 100 and 10,000 persons/km^2 and when p is close to 2, the density of population is less than 100 persons/km^2. As for the type of land use, a fuzzy interval states the membership of the values of p to the set of the variable, i.e. the degree to which the different population densities belong to the site considered. Examples are given in Fig. 2b, 3b, 4b.

Table 1: Categories of noise levels

Category	Noise level intervals w [dB(A)]	Mean population density
Noisy urban residential	58 to 72	25,000 persons / km^2
Urban and quiet residential	48 to 58	1,200 persons / km^2
Rural	20 to 48	< 100 persons / km^2

2.1.4 Crisp and fuzzy quality assessment

Given a quality range in the interval [0,10], the following crisp function q (**Fig. 1**) is considered (adapted from Enea et al. 2001).

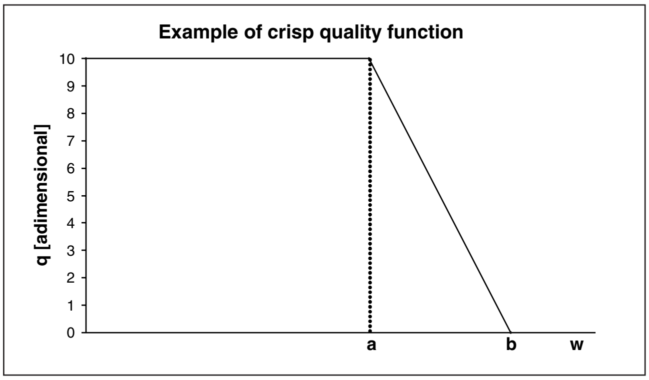

Fig. 1: Crisp quality function

$$q = \begin{cases} 10 & \text{if } w \le a \quad a = 60 + 10p - 10l^{3,4} \\ \dfrac{10}{a-b}w - \dfrac{10b}{a-b} & \text{if } a < w < b \\ 0 & \text{if } w \ge b \quad b = 100 + 10p - 40l \end{cases} \tag{1}$$

w usually ranges from 20 to 120 dB. The values in **Table 2** show that for the same type of land use and existing noise level w, the quality is lower when the population density is lower too. For the same population density and existing noise level w, the quality is lower when the type of land use is rural. For the same population density and type of land use, lower is the quality, higher is the existing noise level w. These results seem to be coherent with the concept of quality of a site with respect to noise impacts. When the primitives are expressed by fuzzy numbers and intervals, the quality function is fuzzified by means of the Extension Principle (for details see, for example, Wang et al. 1992). Employing this principle, standard arithmetic operations on real numbers are extended to fuzzy numbers, as the following:

$$[Q(W,P,L)](q) = \sup_{(w,p,l)/q=q(w,p,l)} \min(W(w), P(p), L(l)) \tag{2}$$

2.2 Fuzzy evaluation of LCI noise emissions

LCI noise emissions of each unit process can be expressed by noise levels. The sources of noise, i.e. all the machines and equipments working in the process, should be identified and the ranges of levels related could be estimated by means of literature data (e.g. Canter 1996). The noise levels have to be linked to the functional unit considered: equipments usually work continuously so it is assumed that the noise emissions inventoried do not vary during all the time related to the functional unit. Noise could be attenuated by natural barriers, such as vegetation. Spatial propagation and attenuation can be estimated by simple models, based on the geometry of the source (punctual, linear or plane) and linear attenuation coefficients, or by mathematical modelling of the propagation of the sound wave (Canter 1996, Morris et al. 1996). For the goal of this paper, propagation and attenuation are not considered. The noise levels of different sources can be finally aggregated in order to obtain an overall level l_{PTOT} for each unit process, according to the following expression:

$$l_{PTOT} = 10\log\frac{1}{t}\left(\sum_n t_n \times 10^{\frac{l_{P,n}}{10}}\right) \tag{3}$$

where t is the total duration time of all the noise sources and t_n the duration time of the source n.

The fuzzification of l_{PTOT} consists of the transformation of each noise level into a fuzzy number and then in the application of the extension principle:

$$[L_{PTOT}(L_P)](l_{PTOT}) = \sup_{(l_{P,n})/l_{PTOT}=l_{PTOT}(l_{P,n})} \min(L_{P,n}(l_{P,n})) \tag{4}$$

2.3 Noise impact assessment

The impact due to the overall noise level l_{PTOT} depends on the target exposure, represented by the population exposed pe [persons] and the time of exposure t [h], on the effect, represented by the nuisance nf [adimensional] felt by a representative sample of population, and on the quality of the site.

2.3.1 Population exposed and time of exposure

If a spatial differentiation was considered for the evaluation of the LCI noise emissions, the same should be considered for the calculation of the population exposed. In this paper, the population exposed is assumed to be constant and can be expressed by a crisp (pe) or a fuzzy (PE) number built on the information collected. Since it is supposed that the sources of noise work continuously, the time of exposure equals the time related to the functional unit. Otherwise, it has to be estimated by the practitioner on the basis of his knowledge and the information available, by a crisp (t) or a fuzzy (T) number.

2.3.2 Nuisance function

The nuisance should be elicitated by means of interviews and tests on a representative sample of population and could depend on: the noise level l_{PTOT}, which is independent from

Table 2: Examples of possible values of (a, b) for different couples (p, l)

(p, l)	(0, 0)	(1, 0)	(2, 0)	(0, 1)	(1, 1)	(2, 1)	(0, 1.5)	(1, 1.5)	(2, 1.5)
a	60	70	80	50	60	70	20	30	40
b	100	110	120	60	70	80	40	50	60

the nature of the noise; the distribution of frequencies of $l_{P\,TOT}$; the existing noise level w prior to the impact and the nature of the population exposed. The development of specific nuisance functions for each unit process is difficult due to the time and the resources needed. In this paper, the following function developed for traffic noise is considered (Nielsen et al. 2000):

$$nf = 0.01 \times 4.22^{0.1(l_{PTOT} - w)} \tag{5}$$

where

l_{PTOT} = overall noise level of the process, [dBA]
w = existing noise level, 20 dBA
nf = nuisance due to the noise level, [adimensional]

It should be noted that, since traffic noise has a rather uniform frequency distribution, this function is able to represent all the types of noise. So it is acceptable to adopt it for sources other than traffic.

2.3.3 Impact assessment

When the variables involved in the evaluation are expressed by crisp numbers, the noise impact [adimensional] could be expressed as the following:

$$imp = \left(\frac{pe \times t}{p_{tot} \times t_{tot}} \right) \times nf \times q \tag{6}$$

p_{tot} = total population potentially exposed [persons]
t_{tot} = total duration of the noise level [h]

The higher q, pe, t and nf are, the higher is the noise impact. The scale of the impact values is fully arbitrary and cannot be interpreted in an absolute way.

When the variables are expressed by fuzzy numbers and intervals, the fuzzy impact IMP of the noise level L_{PTOT} is calculated by means of the extension principle:

3 Example: Noise Impact of Coal Mining and Combustion Processes

3.1 Problem description

Three processes (**Table 3**) are considered from an LCA of coal based electricity production (Benetto et al. 2004). Some assumptions were made in order to lower the sophistication:

- only the higher noise impact generated by each process is considered, without aggregating noise emissions according to eq. 3;
- the propagation and attenuation of noise levels are neglected;
- the population exposed and the duration of exposure are assumed to equal, respectively, the total population exposed and the full duration of the noise emissions.

The membership functions of the variables listed in Table 3 are given in **Fig. 2, 3, 4**. These functions are used to assess the noise quality of the related sites.

3.2 Results and discussion

The fuzzy quality and noise impact assessment results are given in **Fig. 5**. The results are coherent with the shapes of the variables of Figures 2 to 4 and their fuzzy nature is more informative than crisp numbers. S1 is a good quality site because the membership degrees of q values from 8 to 10 are high but to some extent quality could be also be poor because the membership degree of values from 3 to 4 cannot be neglected. By similar considerations, it can be stated that the quality of S2 is rather medium-low and the quality of S3 is rather low. Such nuanced appreciations of the quality are difficult to be obtained by classical crisp approaches. Noise impact is less significant in S3 than in the other processes mainly due to the worse quality of the site prior to LCI emissions and to the lower LCI noise levels than in S1 and S2. The shapes and magnitudes of the impacts of S1 and S2 are fully pertinent with the variables describing the sites and with their quality. Again, the membership functions show a variety of plausible impact values to be considered for interpretation. A significant drawback is that impact results are

$$[IMP(PE,T,NF,Q)](imp) = \sup_{(pe,t,nf,q)/imp=imp(pe,t,nf,q)} \min\left(PE(pe), T(t), NF\left(L_{PTOT}, W\right), Q(q)\right) \tag{7}$$

Table 3: Variables for the noise impact assessment of coal mining and combustion

	Variables			
Processes	**Type of land use**	**Population density**	**w**	**l_P**
S1: open cast and underground coal mining	Rural	less than 100 persons/km^2	triangular fuzzy number with height = 32 dBA over the interval [20,48]	triangular fuzzy number with height = 100 dBA over the interval [90,110]
S2: open cast coal mining	Less rural and more residential	between 100 persons/km^2 and 1,000 persons/km^2	triangular fuzzy number with height = 42 dBA over the interval [30,58]	triangular fuzzy number with height = 100 dBA over the interval [90,110]
S3: combustion in travelling grate combustor	Urban	between 1,000 persons/km^2 and 10,000 persons/km^2	triangular fuzzy number with height = 57 dBA over the interval [45,73]	triangular fuzzy number with height = 90 dBA over the interval [80,100]

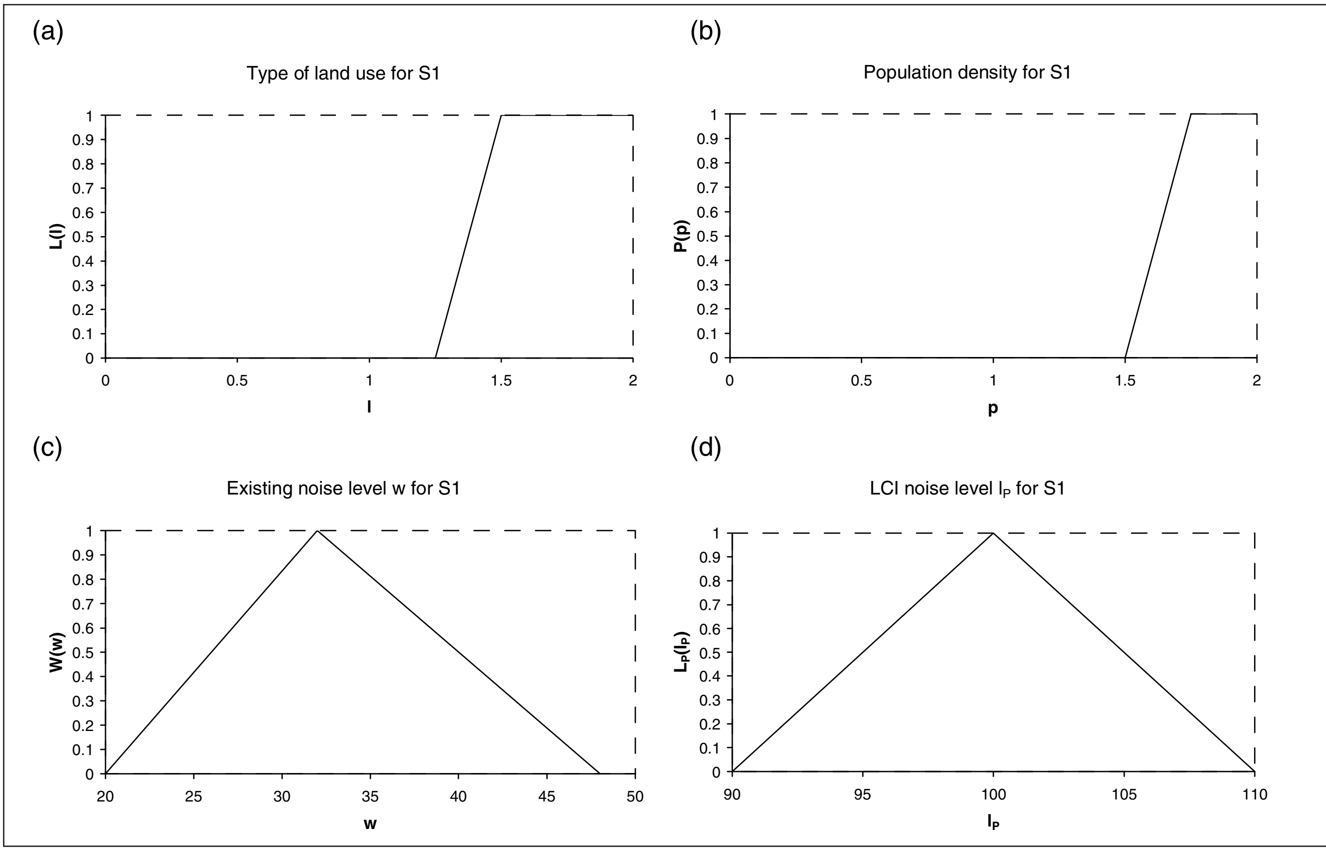

Fig. 2: Membership functions of the variables for S1

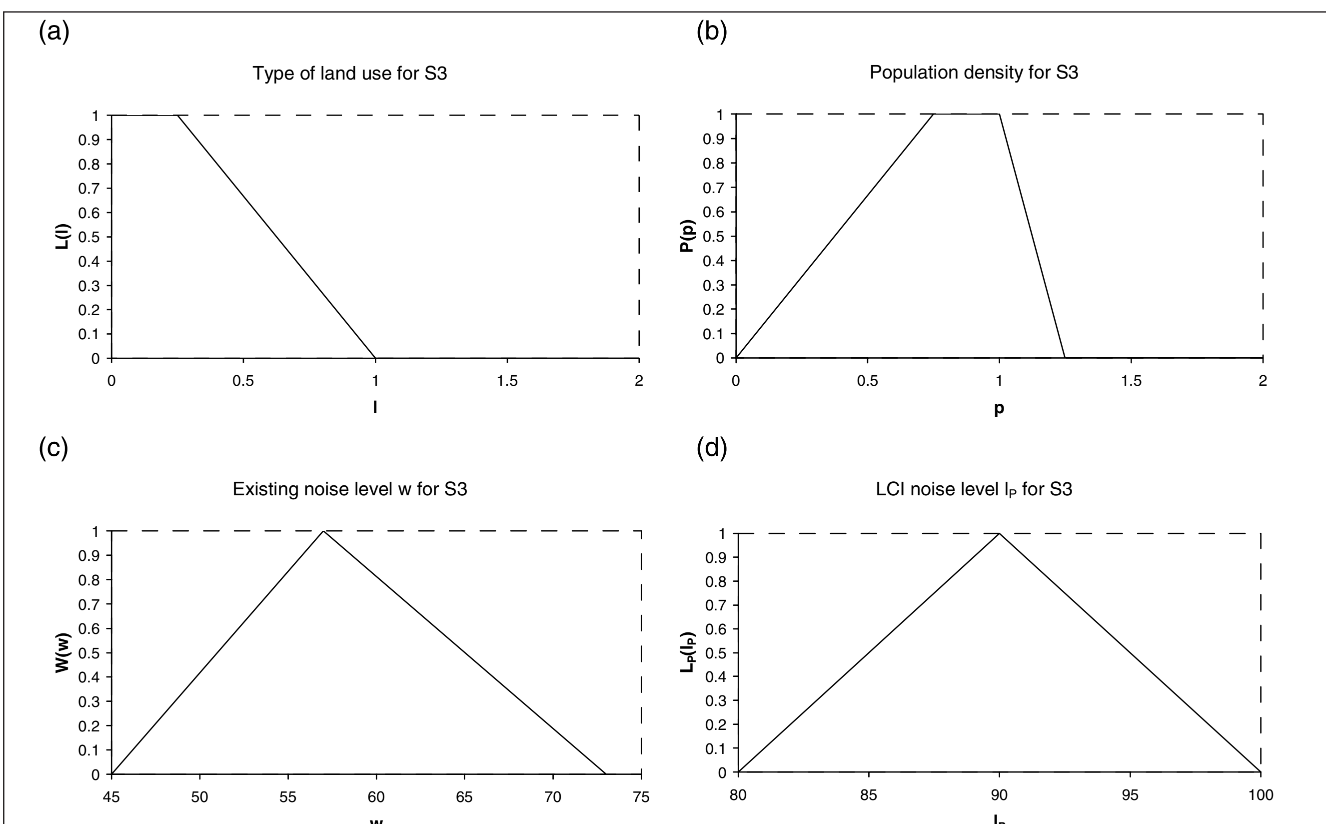

Fig. 3: Membership functions of the variables for S2

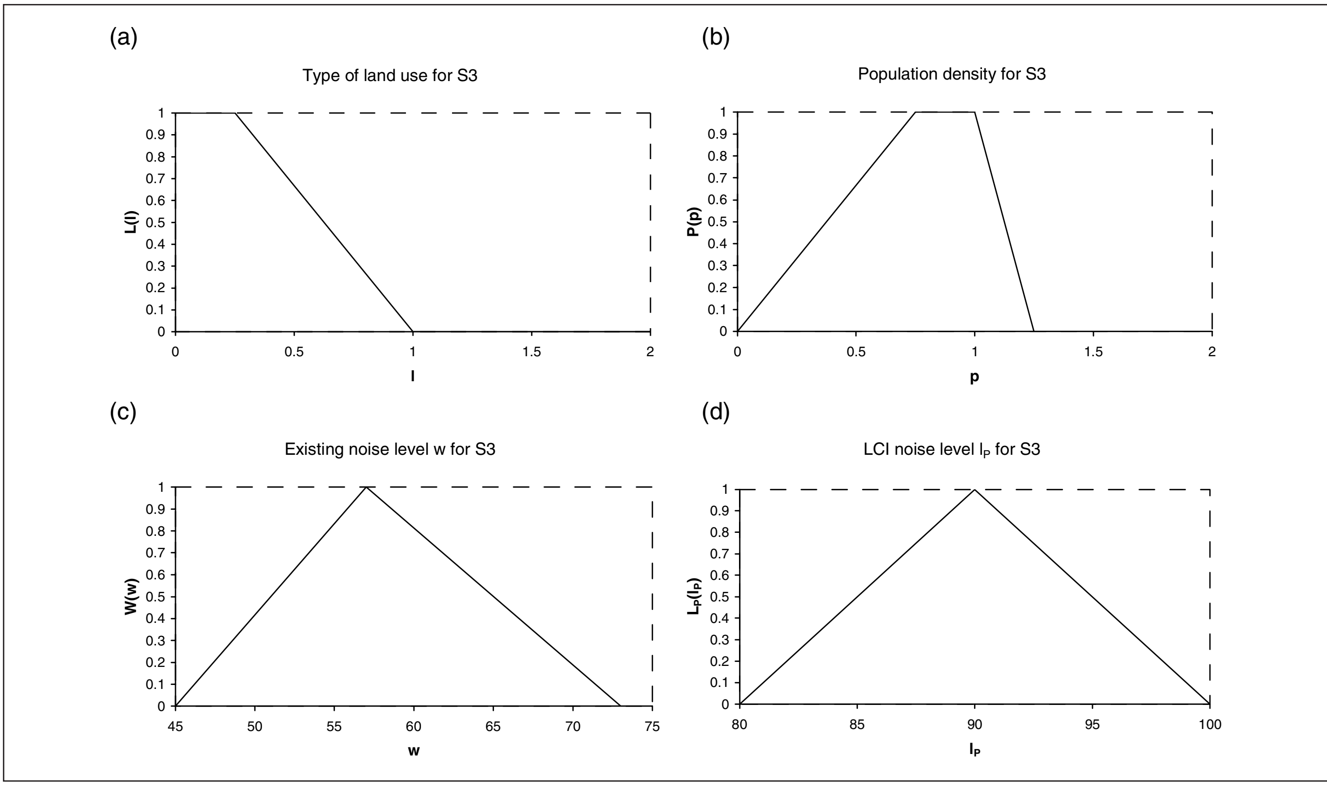

Fig. 4: Membership functions of the variables for S3

adimensional and have no clear physical meaning, due to the impact function chosen (eq. 6) and to the abstract x-scale of p and L. Further investigation is needed to obtain more intelligible results. In the hypothesis of having to compare noise impact results (e.g. of concurrent product systems), fuzzy membership functions can be compared by means of semantic distances (e.g. Dujet et al. 1999).

4 Conclusion and Outlook

The application example proved the operationability of the method for fuzzy noise impact assessment presented. The simplifications adopted are not supposed to affect the significance of this result: considering the spatial differentiation of emissions and targets, more primitives or more linguistic variables do increase the complexity of calculations, but should not change the nature of results and conclusions. The variables involved in the assessment (the quality of the site, the nuisance felt by a population sample, the type of land use, …) were expressed by fuzzy intervals and numbers, allowing a higher degree of flexibility and continuity than in crisp assessment methods, thus avoiding the need of sensitivity analysis, because abrupt changes in the results are unlikely. Fuzzy impact results are more informative for interpretation than crisp ones, because of the membership functions showing a wide range of likely and unlikely values characterized by a degree of plausibility, i.e. of membership to the linguistic category or definition related. The application of the method also showed shortcomings. The variables involved should be issued from a consensus gained in an expert panel or at least between relevant actors of the process and should be tested and developed in more detail. For example, the crisp function describing the noise impact (eq. 6) leads to adimensional impact values without clear physical meaning. Also, the use of fuzzy-sets still increase sophistication. For instance, the comparison of noise impacts expressed by fuzzy numbers or interval requires the use of semantic distances, that are more complicated that usual distances.

Nevertheless, by reducing sophistication as much as possible, and by setting the primitives and variables on a basis of consensus, the fuzzy approach presented seems to be promising for the treatment on noise effects in LCA studies.

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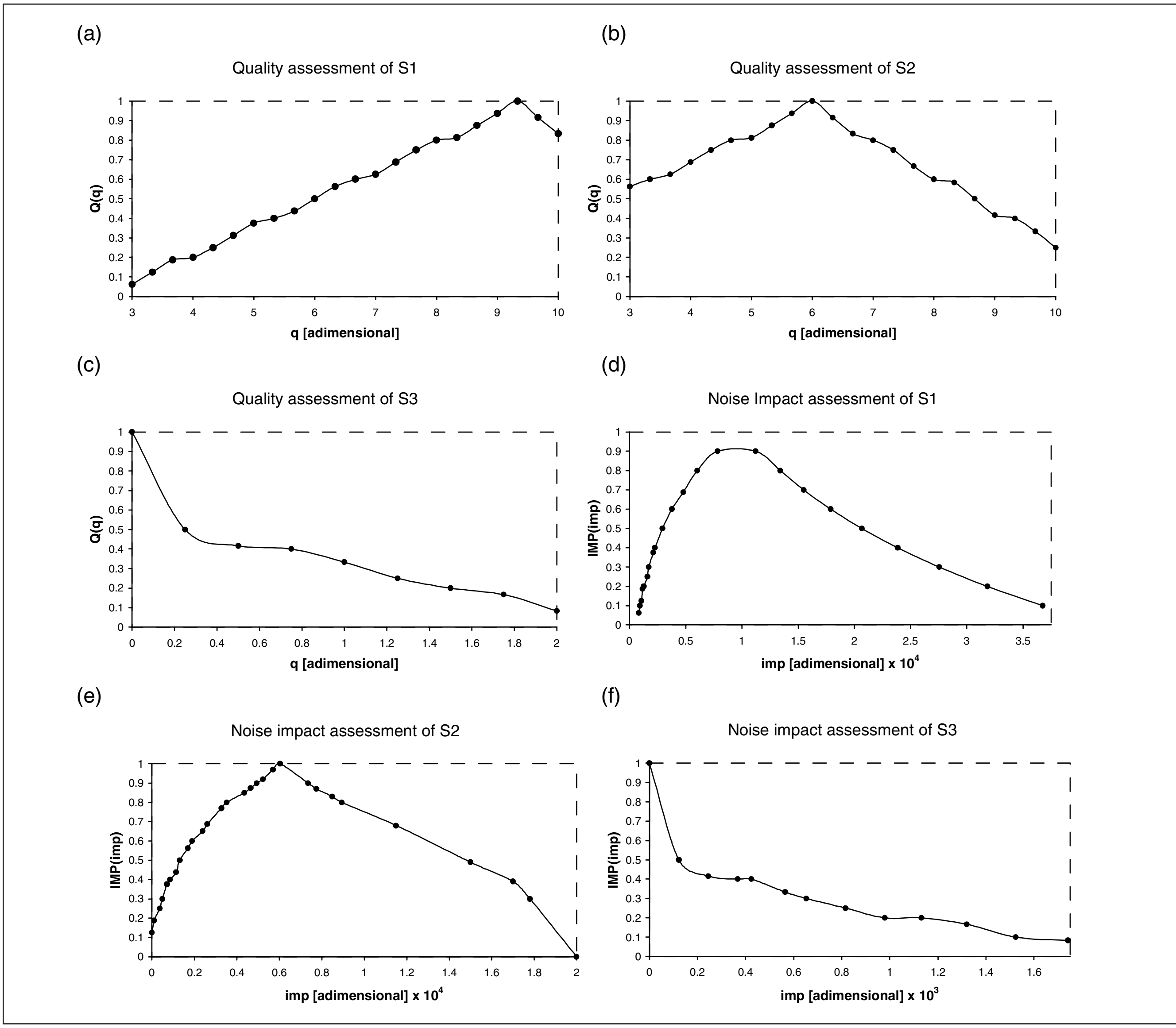

Fig. 5: Fuzzy quality and impact assessment results

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